Optimization of Cutting Parameters for Turning XC38 Steel Using the Taguchi Method

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Abstract: Increasing cutting tool lifespan is essential for boosting manufacturing efficiency and profitability. Fewer tool replacements reduce costs and production interruptions. Longer tool life ensures consistent, high-quality products, vital for competitive advantage and customer satisfaction. This study explores how magnetic fields and cutting parameters affect tool performance during machining. Using the Taguchi method for optimization, we found that applying a magnetic field with optimized parameters significantly enhances tool durability. Our data showed a 99.58% match with our predictive model, demonstrating reliability and practical application. These techniques can greatly improve tool longevity, enhancing operational efficiency and profitability.

Keywords: Tool wear, Taguchi method, Optimization, Manufacturing, Cutting parameters.

1. INTRODUCTION

Tool wear is a pivotal concern in manufacturing, as it directly affects the quality of machined surfaces and the durability of cutting tools. Factors such as magnetic fields and cutting parameters are integral to influencing tool wear. When applied correctly, magnetic fields during machining can significantly reduce tool wear and enhance surface finish; this effect varies with the intensity and orientation of the magnetic field. Additionally, cutting parameters—including cutting speed, feed rate, and depth of cut—play a vital role in determining the amount of heat generated and the cutting forces experienced, both of which are crucial in influencing tool wear. This research explores the synergistic effects of magnetic fields and cutting parameters, aiming to identify optimal conditions that minimize tool wear and thereby improve overall manufacturing efficiency and productivity.

“(T. Ozel et al., 2005)”, “applied neural network models to predict surface roughness and tool flank wear in finish hard turning, demonstrating superior performance compared to regression models using AISI 52100 and AISI H-13 steels”. “(L.J. Xie et al., 2005)”,” simulated chip formation through FEM in ABAQUS and developed a validated Python-based tool wear estimation program”. “(A. Altin et al., 2007)”, “investigated the impact of cutting speed on tool wear in machining Inconel 718, identifying distinct wear patterns for SNGN and RNGN inserts”. “(M.A. Xavior et al., 2009)”,” discovered that using coconut oil significantly reduced tool wear and enhanced surface finish during the turning of AISI 304”. “(P. Bansal et al., 2013)”, “observed that increased alumina content in aluminum metal matrix composites enhanced mechanical properties”. “(M.S.H. Bhuiyan et al., 2014)”, “employed acoustic emission and vibration signatures to monitor tool wear, chip formation, and surface roughness”. “(Yadav et al., 2015)”, “validated DEFORM 3D simulations of turning Inconel 718 with experimental data”. “(S. Debnath et al., 2016)”, “determined optimal cutting conditions for surface roughness and tool wear in CNC turning of mild steel”. “(R.W. Maruda et al., 2017)”, “found that MQCL with a phosphate ester-based additive reduced tool wear in AISI 1045 carbon steel”. “(W. Grzesik et al., 2018)”, “assessed the wear resistance of TiAlN/AlTiN-coated tools in finish turning Inconel 718”. “(R. Çakıroğlu et al., 2020)”, “optimized EDM parameters for AISI L2 steel, enhancing MRR, TWR, and Ra”. “(C. Agrawal et al., 2021)”, “reported that cryogenic turning improved tool life and surface roughness in Ti–6Al–4V”. “(K. Singh et al., 2022)”, “achieved a reduction in TWR during HSLA steel machining with EDM using the Taguchi method”. “L. (Patnaik et al., 2022)”, “validated FEM analysis of 316 LVM stainless steel machining with experimental data”. “(G. Jovicic et al., 2023)”, “optimized dry turning of Inconel 601 using a neural network and genetic algorithm”.

Most studies examined how machining parameters—cutting speed, feed rate, and depth of cut—impact turning performance, focusing on surface roughness, tool life, machining time, and tool wear rate. Experimental research is costly and time-consuming due to numerous experiments. To address this, researchers use empirical modeling techniques like the Taguchi method, ANN, fuzzy logic, RSM, and linear regression to understand input-output relationships. These methods efficiently gather data, reduce noise, and define statistical characteristics. Despite advancements, predicting tool wear rate numerically is still underdeveloped. This study proposes using the Taguchi method to predict tool wear rate and explores the effect of a magnetic field on tool wear during turning.

2. PROCEDURE

2.1 Analysis method

The Taguchi method is a robust statistical technique widely used in engineering and manufacturing to optimize processes and enhance quality. This method involves systematically varying parameters through the use of orthogonal arrays to design experiments efficiently, thereby minimizing the number of trials required. By focusing on making products and processes less sensitive to variations, the Taguchi method achieves high performance with reduced cost and effort. Its primary objective is to identify optimal conditions that reduce variability and improve average performance, ultimately leading to improved product reliability and process optimization.

2.2 Materials

The methodology of this study is depicted in Figure 1. The investigation was conducted on workpieces made from XC38, characterized by the following chemical composition: 0.38% carbon, 0.66% manganese, 0.27% silicon, 0.035% sulfur, 0.035% phosphorus, 0.4% nickel, 0.4% chromium, and 0.1% molybdenum. The cutting tools used as inserts were manufactured from sintered metal carbide, primarily consisting of tungsten carbide (WC). To enhance specific properties, additions of titanium carbide or tantalum were included. These carbides are notable for their high refractoriness and exceptional hardness. The cutting inserts employed, shown in Figure 1, are detachable and rhombic, made from P25 grade metal carbide (type CCMT09T308E-73), featuring a rounding radius of 0.8 mm. All the experimental results are summarized in Table 2.

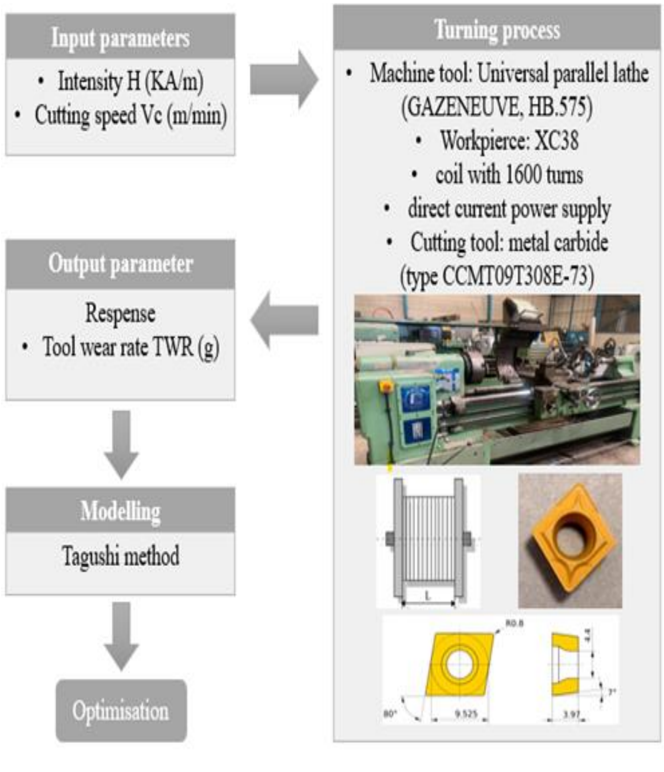

Figure 1. Experimental scheme.

2.3 Factors and their levels

Based on multiple studies, two cutting parameters—cutting speed and intensity—were selected along with their respective levels. The experimental conditions are detailed in Table 1.

Table 1. Cutting parameters and their respective levels

	Cutting parameters	**Levels of factors**			
		L1	**L2**	**L3**	**L4**
I	Intensity (KA/m)	0	5.5	16.5	28.5
Cs	Cutting speed (m/min)	18	48	82	136

After developing the tests, the subsequent step involves analyzing the results and optimizing the cutting parameters to evaluate their statistical significance. Analysis of Variance (ANOVA) and the Signal-to-Noise (S/N) ratio were utilized to determine the effect of each parameter on the tool wear rate (TWR).

2.4 ANOVA variance

The statistical method of ANOVA is instrumental in both identifying the influence of parameters contributing to a series of experimental outcomes and interpreting the experimental data. The coefficient of determination, (R^2) represents the proportion of explained variance to total variance and serves as a crucial metric for assessing model fit. A response model that closely approximates real data will have an (R^2) value approaching unity.

Table 3 presents the ANOVA results for Tool Wear Rate (TWR), with the analysis conducted for probability (P) values less than 0.05, corresponding to a confidence level of 99.86%.

2.5 Signal-to-noise ratio (S/N)

Taguchi utilized the Signal-to-Noise Ratio (S/N) as the preferred quality characteristic for data analysis. This approach categorizes quality characteristics into three types:

1. Larger-the-better.
2. Nominal-the-best.
3. Smaller-the-better.

For our study, where minimizing tool wear rate is critical, the "smaller-the-better" category was selected. The formula to compute the S/N ratio for the "smaller-the-better" category (expressed in decibels) is provided below:

$$S/N_{STB} = -10log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \qquad (1)$$

Here, n denotes the number of repetitions for each experiment, and y represents the observed value of the cutting tool wear.

The optimal parameter level is determined by the highest signal-to-noise (S/N) ratio. The experimental data were analyzed using Minitab 21 statistical software, and the calculated S/N ratios are presented in Table 2. This analysis highlights the main effects of the cutting parameters on the tool wear rate (TWR).

3. RESULTS AND DISCUSSION

A. The influence of cutting parameters (Cs, I) on tool wear rate (TWR).

Table 3 of the ANOVA analysis reveals that intensity (I) is the most influential factor on cutting tool wear, contributing 99.24% to the model. An increase in intensity leads to parallel streaks in the direction of the cutting speed, attributed to machining kinematics. Additionally, cutting speed significantly impacts tool wear, accounting for 0.68% of the variation, due to the extended contact length between the tool and the workpiece.

B. Analysis of the main effects of the Signal-to-Noise (S/N) Ratio on tool wear rate (TWR)

Table 4 and Figure 2 illustrate the impact of the two examined parameters on tool wear rate (TWR). The most significant factor is intensity, with an influence value of 0.008, followed by cutting speed (Cs), which has an effect value of 0.001. According to the Taguchi method, the optimal parameters for minimizing cutting tool wear (TWR) are a cutting speed (Cs) of 136 m/min and an intensity (I) of 16.5 KA/m, as depicted in Figure 2.

Table 2. Experimental results

N°	**Cutting parameters**		**Response**	**S/N Ratio**	
	Intensity (KA/m)	**Cutting speed (m/min)**	**Tool wear rate (g)**	Y_{TWR}	Y^2_{TWR}
1	0	18	3.6590	-11.2672	126.9498
2	0	48	3.6588	-11.2668	126.9407
3	0	82	3.6585	-11.2661	126.9250
4	0	136	3.6581	-11.2651	126.9025
5	5.5	18	3.6653	-11.2822	127.2880
6	5.5	48	3.6651	-11.2817	127.2768
7	5.5	82	3.6648	-11.2810	127.2610
8	5.5	136	3.6645	-11.2803	127.2452
9	16.5	18	3.6569	-11.2623	126.8394
10	16.5	48	3.6568	-11.2620	126.8326
11	16.5	82	3.6567	-11.2618	126.8281
12	16.5	136	3.6566	-11.2615	126.8214
13	28.5	18	3.6576	-11.2639	126.8754
14	28.5	48	3.6573	-11.2632	126.8597
15	28.5	82	3.6570	-11.2625	126.8439
16	28.5	136	3.6567	-11.2618	126.8281

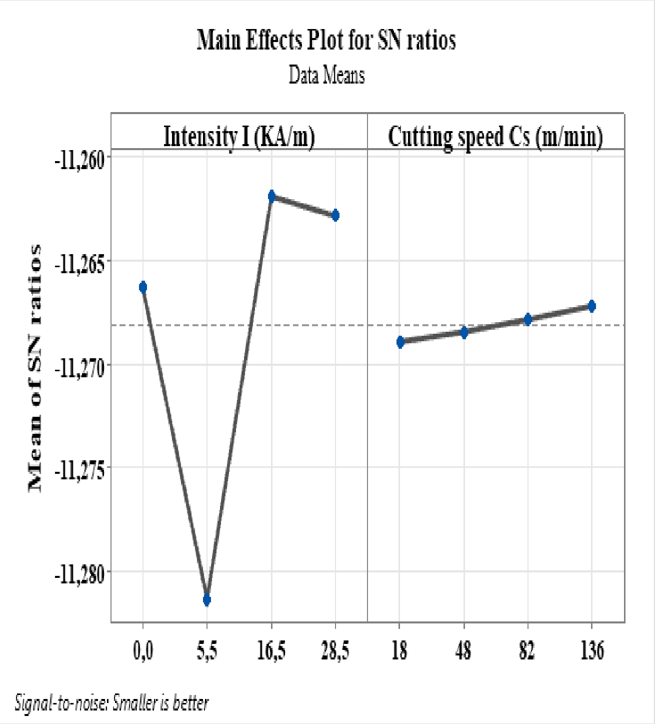

Figure 2. Main effects plot for S/N ratio.

C. Analysis of relationships using regression technique

Regression analysis is a statistical method utilized to model the relationship between a dependent variable and one or more independent variables. This approach helps in understanding how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed.

The normal probability plot shows the deviation of individual values from the regression model equation. Points closely grouped around the line indicate minimal deviation.

Residual plots for tool wear are displayed in Fig. 4. The nearly linear response of the normal probability plot suggests that the errors are normally distributed.

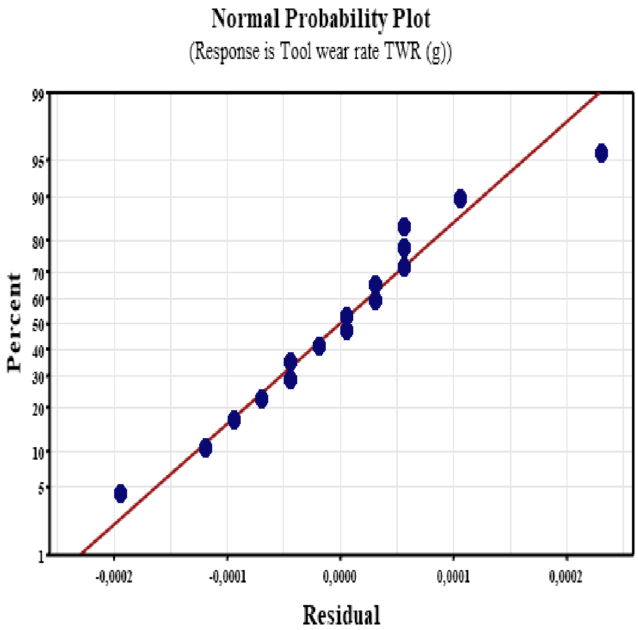

Figure 4. Residual graphs for the signal-to-noise ratios of the tool wear rate.

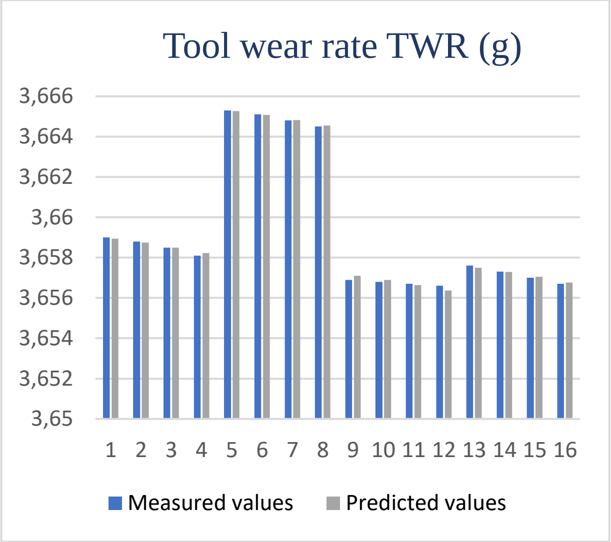

Figure 3. Comparison between measured and predicted values of TWR.

Table 3. ANOVA variance.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Intensity (KA/m)	3	0.0001730	99.24%	0.0001730	0.00005766	3563.37	0.00000000000004
Cutting speed (m/min)	3	0.0000012	0.68%	0.0000012	0.00000039	24.35	0.00011837160234
Error	9	0.0000001	0.08%	0.0000001	0.00000002		
Total	15	0.0001743	100%				

Table 4. Response table for means.

Level	**Intensity (KA/m)**	**Cutting speed (m/min)**
1	3,659	3,660
2	3,665	3,660
3	3,657	3,659
4	3,657	3,659
Delta	0,008	0,001
Rank	1	2

In this study, regression analysis was employed to determine the equations for predicting tool wear rate. These predictions were represented by a linear model.

Equation 6 depicts the predicted linear equation for the output parameter. The R^2 value achieved through the linear regression model was 99.92% for tool wear rate. Figure 5 displays a comparison between the predicted values and the experimental results, demonstrating a strong correlation between them.

The regression equation is:

$$TWR = 3{,}66179 - 0{,}000158 \times H - 0{,}000006 \times Vc \qquad (2)$$

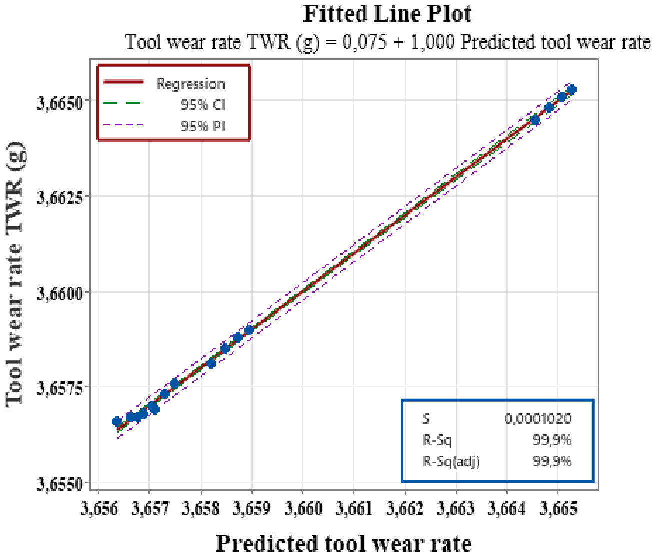

Figure 5. Comparison of the linear regression model with experimental results for tool wear rate.

6. CONCLUSIONS

This study examined various cutting parameters, including cutting speed and intensity, during the turning of XC38 steel to enhance the performance of cutting tools. The investigation employed the Taguchi optimization method and Analysis of Variance (ANOVA) to quantify the impact of each parameter on cutting tool wear.

L'analyse de variance (ANOVA) a révélé que le coefficient de détermination (R^2) du modèle d'usure des outils de coupe (TWR) est très élevé, atteignant 99,92 %. Cela indique une excellente concordance entre les valeurs expérimentales et les valeurs prédites. Concernant l'impact des différents paramètres, il a été conclu que l'intensité est le facteur le plus influent sur le TWR.

Optimization using the Taguchi single-objective method was conducted with a focus on the signal-to-noise (S/N) ratio. This analysis determined that the optimal parameters for minimizing tool wear rate are a cutting speed (Cs) of 136 m/min and a (I) of 16.5 KA/m.

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